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Production cost minimization through optimization

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ABSTRACT

Delayed raw material delivery is a persistent supply chain problem in apparel manufacturing, often causing material shortages, production disruptions, productivity losses, and increased operating costs. Although various supplier selection approaches have been developed, relatively limited research has integrated the economic consequences of supplier performance with multidimensional supplier evaluation to support cost-oriented procurement decisions. This study therefore proposes and validates an integrated supplier selection framework that combines Cost Ratio Analysis (CRA) and Dimensional Analysis (DA) to improve supply chain performance and minimize production losses associated with delayed material delivery. A quantitative industrial case study was conducted using operational data from two apparel manufacturing companies in Bangladesh. CRA was employed to quantify the financial impact of supplier-related delivery delays, while DA was used to rank supplier alternatives according to multiple operational performance criteria. The integrated framework was subsequently applied to identify the most appropriate suppliers for timely raw material procurement. The results demonstrate substantial improvements following supplier selection, with the benefit-to-cost ratio increasing by 50% and on-time raw material delivery improving from 60% to 94%. These improvements contributed to an approximately 20% increase in production efficiency and reduced productivity losses attributable to material shortages. The principal novelty lies in integrating economic impact quantification through CRA with multidimensional supplier ranking through DA within a single, practical decision-support framework validated using real industrial data. The framework provides apparel manufacturers with a transparent and cost-oriented approach for supplier evaluation, strategic sourcing, and production planning, thereby strengthening supply chain reliability, operational efficiency, and competitiveness.

1. Introduction

Enhancing efficiency and competitiveness in apparel manufacturing strongly depends on establishing a reliable and responsive supply chain system. Since apparel manufacturers frequently rely on imported raw materials, including fabrics, accessories, and specialized components, effective supply chain coordination has become essential for maintaining production continuity, controlling operational costs, and satisfying customer delivery requirements. However, despite continuous improvements in supply chain management practices, many apparel manufacturers still experience significant challenges related to delayed raw material procurement, inconsistent supplier performance, and unexpected production interruptions. These challenges are particularly critical in developing apparel-producing countries where manufacturers operate under strict international delivery schedules and cost pressures.

A major contributor to these challenges is the conventional supplier selection process adopted by many apparel organizations. In practice, supplier selection decisions are often based on product price, previous business relationships, personal recommendations, or informal communication through telephone and email rather than systematic evaluation of supplier capabilities. Although such approaches may provide short-term purchasing advantages, they frequently neglect important supplier performance dimensions, including delivery reliability, product quality, service capability, responsiveness, and long-term operational sustainability. Consequently, manufacturers may select suppliers offering lower purchase prices but generating higher hidden costs due to delayed deliveries, quality failures, production interruptions, and emergency procurement activities. In recent years, supply chain management practices in the apparel industry have received increasing attention, including the implementation of green supply chain concepts and sustainable procurement strategies [1]. However, sustainability-oriented initiatives alone cannot ensure operational efficiency unless supplier selection decisions are supported by reliable evaluation mechanisms. Therefore, supplier selection has evolved from a simple purchasing activity into a strategic decision-making process that directly influences organizational performance, production efficiency, and competitive advantage [2].

The importance of supplier selection becomes more evident considering the complexity of modern apparel supply chains. Delivery uncertainty has been identified as one of the major sources of supply chain risk, requiring organizations to evaluate suppliers based on multiple criteria rather than relying on a single factor such as purchasing cost [3]. Previous studies have emphasized that supplier evaluation should incorporate critical criteria, including cost, quality, delivery performance, and service capability [4]. Therefore, developing a systematic supplier evaluation framework that integrates both operational performance and economic consequences is essential for improving supply chain reliability and minimizing production losses. Supplier selection has been extensively investigated as a multi-criteria decision-making problem because organizations must balance conflicting objectives, including cost reduction, quality improvement, delivery reliability, and supplier flexibility. The early contributions of Dickson established fundamental supplier evaluation criteria, while later studies expanded these criteria by incorporating additional operational and strategic factors. Weber et al. further demonstrated that cost, quality, and delivery performance remain among the dominant supplier selection considerations across industries. Recent surveys involving procurement professionals also confirmed that these criteria continue to represent the primary factors influencing supplier decisions [5].

Although traditional supplier selection studies provide valuable foundations, many approaches primarily focus on identifying the relative importance of evaluation criteria rather than quantifying the actual operational and financial consequences of poor supplier performance. For example, several researchers have emphasized the importance of establishing supplier–buyer relationship structures before determining evaluation criteria [6]. Similarly, supplier assessment frameworks have classified selection criteria into major categories such as cost, logistics, quality, innovation, and management capability, while other studies have proposed additional dimensions, including technology adoption and service performance [7], [8]. These studies demonstrate the multidimensional nature of supplier evaluation; however, they provide limited guidance regarding how supplier performance failures translate into measurable production cost impacts. Various analytical approaches have been proposed to improve supplier selection decisions, including cluster analysis, statistical methods, data envelopment analysis, decision support systems, total cost of ownership models, and mathematical programming techniques [9]–[12]. These approaches have significantly contributed to improving supplier ranking and decision accuracy. However, many existing models evaluate suppliers based on performance scores or preference values without explicitly incorporating the economic losses caused by unreliable deliveries. As a result, a supplier achieving a favorable ranking may still generate substantial production losses if delivery delays create production interruptions, overtime requirements, or expedited transportation costs.

Recent developments in supply chain optimization have introduced advanced computational approaches for improving supplier decision-making. Artificial intelligence-based techniques, including Artificial Neural Networks (ANN), Genetic Algorithms (GA), and simulation-based optimization approaches, have demonstrated potential for predicting supplier performance and optimizing complex supply chain systems [13]–[17]. However, these approaches often require extensive historical datasets, computational resources, and model development procedures, which may limit their practical implementation in many apparel manufacturing organizations, particularly small and medium-sized enterprises. Furthermore, although mathematical optimization approaches have contributed significantly to supply chain decision-making, their effectiveness depends on the availability of accurate input parameters and appropriate model assumptions. In practical industrial environments, supplier performance evaluation frequently involves incomplete information, uncertain delivery conditions, and changing operational requirements. Therefore, there remains a need for practical and transparent supplier evaluation frameworks that can be easily implemented using available industrial data while simultaneously considering operational performance and financial consequences.

Previous studies have also investigated supply chain optimization from various perspectives, including general supply chain management [18], green supply chain practices [19], global supply chain design [20], and multi-objective optimization approaches [21]. These studies confirm that supplier evaluation represents one of the most critical activities in purchasing management because it directly influences production continuity and organizational performance [22], [23]. However, most existing research focuses either on supplier ranking methodologies or supply chain optimization models, while limited attention has been given to integrating supplier performance evaluation with direct production cost implications [24], [25]. Furthermore, some researchers have emphasized that successful supplier management requires not only selecting appropriate suppliers but also conducting systematic supplier evaluations before decision-making [26]–[54]. Mathematical analyses have further demonstrated the capability of ANN models to accurately identify optimal suppliers.

Recent studies have applied multi-criteria decision-making approaches to supplier evaluation in textile and apparel industries. Wang et al. [44] developed a multi-criteria supplier selection model for textile industries by considering several conflicting operational criteria. Similarly, recent apparel-focused studies have incorporated sustainability, expert preferences, and quantitative ranking approaches using hybrid AHP-TOPSIS and SWARA-TOPSIS frameworks [44]–[47]. Although these studies improve supplier ranking accuracy, their primary emphasis remains on identifying the best-performing supplier rather than quantifying the production cost consequences associated with supplier unreliability. Therefore, a gap remains in developing supplier selection frameworks that simultaneously evaluate supplier performance and measure the economic impact of delivery failures.

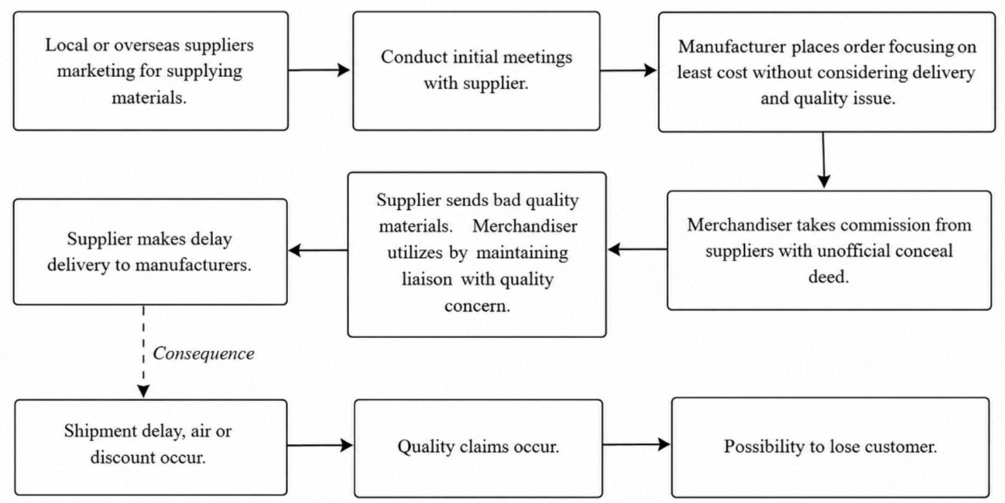

Fig. 1. Traditional suppliers' selection vicious cycle

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Many apparel manufacturers still rely on traditional and informal supplier selection practices based on business relationships, personal referrals, and quoted prices rather than systematic performance evaluation. Such approaches often overlook critical criteria, including quality, delivery reliability, service capability, and long-term supplier performance, resulting in material delays, inconsistent quality, production disruptions, and increased operational costs. Therefore, a structured and data-driven supplier evaluation framework considering multiple criteria such as cost, quality, delivery, and service performance is essential for improving supply chain reliability, minimizing production losses, and enhancing competitiveness in the apparel industry. The consequences of conventional supplier selection practices are illustrated in Fig. 1.

The research contributions of this study are as follows. First, this research proposes an optimization-based supplier selection framework by integrating Cost Ratio Analysis and Dimensional Analysis to improve supplier evaluation in apparel manufacturing. Second, the study validates the proposed framework using real production data from two Bangladeshi apparel factories and demonstrates measurable improvements in on-time material delivery, benefit-to-cost ratio, production efficiency, and production cost minimization compared with conventional supplier selection practices.

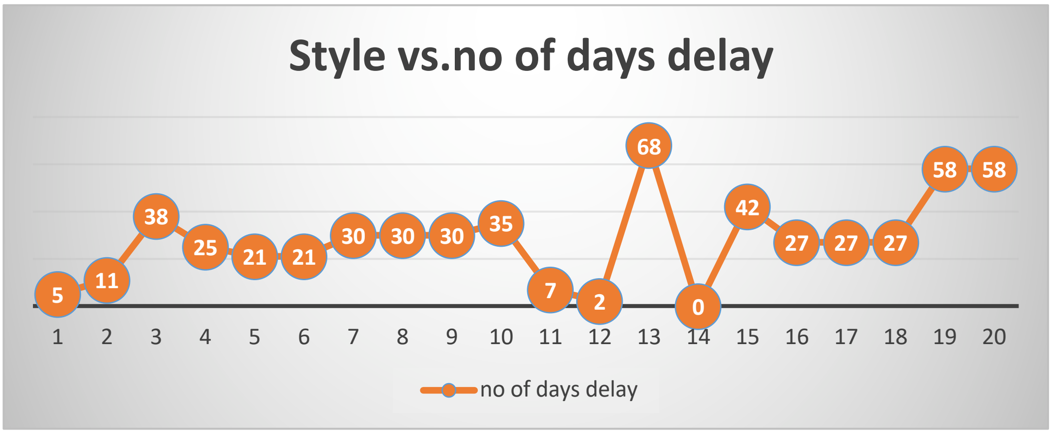

Fig. 2. PO vs. delay status (PU-1)

From Fig. 2, the supplier supplies materials after a minimum of zero days to a maximum of sixty-eight days after the actual delivery date. This is an absurd delivery status. For such delays, the goods must be shipped by air, even if buyers cancel their orders, resulting in a massive loss for the manufacturing unit.

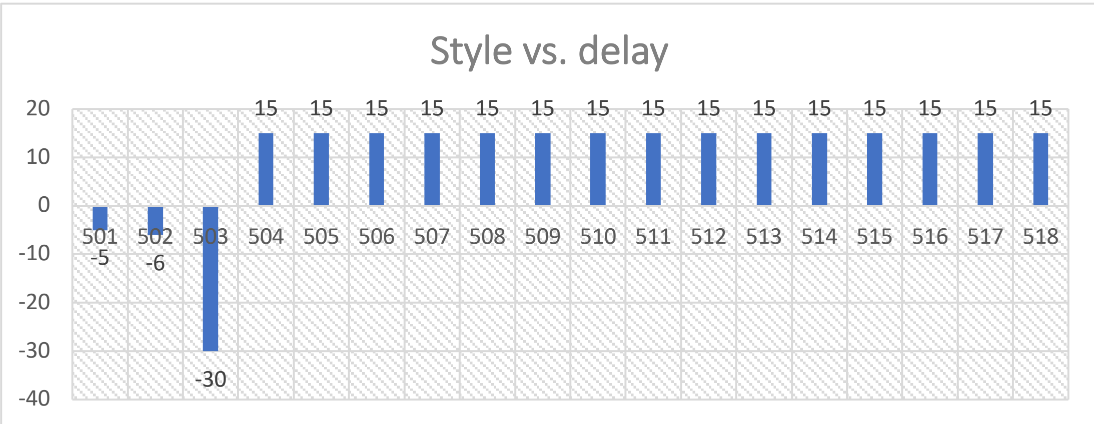

Fig. 3. PO vs. delay status (PU-2)

Similarly, another manufacturing unit suffers from delayed delivery of raw materials. It is found from Fig. 3 that two weeks are delayed for each purchase order. Subsequently, manufacturers have to pay more for air shipment and discount purposes. It happened due to selecting the suppliers without any evaluation prior to the order placement. Customers are thus dissatisfied with placing orders in the same location in the long run. The business is in the risk zone. Many factories had to shut down since they were unable to pay workers' salaries on time due to delayed shipments and their related consequences.

Table 1. Factory wise Income vs. profit loss

Factory	Order quantity	Price	Income	Production cost	Air cost	Discount	Total cost	Profit/ loss
PU1	500000	$0.17	$ 80.000.01	$94.000		$15.001	$111.000	$(30.000.00)
PU2	350000	$0.24	$ 87.500.05	$71.000	$20.001		$91.840	$(3.340.00)

Following the analysis, the financial and operational impacts of conventional supplier selection for Production Units 1 (PU-1) and 2 (PU-2) are summarized in Table 1. For PU-1, the customer placed an order for 500.000 garments at a unit price of $0.16, generating a total revenue of $80.000. However, the production cost increased to $94.000 because additional resources, including overtime operations and extra machinery, were required to compensate for a 20-day delay in raw material delivery. Despite these efforts, the final shipment was delivered approximately two weeks behind schedule, resulting in an 18.75% buyer discount of $15.000. Consequently, the total project cost increased to $111.000, exceeding the total revenue by $30.000 and leading to a substantial financial loss.

Similarly, PU-2 received an order for 350.000 garments with a unit selling price of $0.25, generating a total revenue of $87.500. The manufacturing cost was $71.000; however, delayed material deliveries required the use of air freight, adding an additional $20.001 to the logistics cost. As a result, the total project cost increased to $91.840, exceeding the project revenue by $3.340. These findings demonstrate that delays in raw material procurement significantly increase production and transportation costs, reduce profitability, and negatively affect overall supply chain performance. The analysis highlights the importance of adopting a systematic supplier evaluation and selection framework to minimize delivery delays, reduce operational costs, and improve manufacturing efficiency.

2. Method

2.1. Research Design and Case Study Approach

This study adopts a quantitative industrial case study approach to develop and validate an integrated supplier selection framework for minimizing production losses associated with delayed raw material delivery in apparel manufacturing. The research framework combines Cost Ratio Analysis (CRA) and Dimensional Analysis (DA) to evaluate suppliers based on both economic impact and operational performance. The case study approach was selected because supplier performance evaluation requires real industrial data, including delivery records, production impact, and cost information, which cannot be adequately captured through theoretical modeling alone.

2.2. Case Company Selection and Industrial Context

Two apparel manufacturing companies located in Bangladesh were selected as case organizations. The selection was based on three criteria: (1) active involvement in export-oriented apparel production, (2) availability of historical supplier performance and production records, and (3) experience with raw material delivery delays affecting production schedules. Both companies manufacture garments for international buyers and depend significantly on imported raw materials, making them appropriate cases for evaluating supplier reliability.

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2.3. Data Collection Procedure

Data were collected from multiple operational sources, including purchase orders, supplier delivery records, inventory reports, production planning documents, and supplier evaluation reports. The collected information included supplier delivery dates, actual material arrival dates, material costs, delay duration, production interruption time, and supplier performance indicators. Data collection was performed in collaboration with the procurement and production departments of the selected factories to ensure accuracy and industrial relevance. The data covered the period of 2024-2025, during which supplier delivery performance was monitored.

2.4. Supplier Evaluation Criteria and Measurement

Based on previous supplier selection studies and industrial requirements, four major criteria were considered: cost, quality, delivery performance, and service capability. These criteria were selected because they directly influence production continuity and supply chain efficiency in Table 2.

Table 2. Influence production continuity and supply chain efficiency

Criterion	Definition	Measurement method
Cost	Financial impact of supplier performance	Cost ratio (%)
Quality	Material acceptance/rejection performance	Defect percentage
Delivery	Ability to meet committed delivery dates	On-time delivery (%)
Service	Supplier responsiveness and communication	Performance score

2.5. Determination of Penalty Percentage

The penalty percentages used in Cost Ratio Analysis were derived from the actual economic consequences observed in the case of companies. When delayed deliveries occurred, additional costs were generated through overtime production, expedited transportation, production waiting time, and order adjustment requirements. These cost impacts were converted into penalty ratios relative to the original procurement cost.

2.6. Determination of Weighting Factors in Dimensional Analysis

The weighting factors for supplier evaluation criteria were determined through discussions with experienced personnel from procurement, merchandising, and production departments of the participating companies. The experts evaluated the relative importance of each criterion based on its influence on production continuity and supply chain performance. The final weights were calculated by averaging expert assessments in Table 3.

Table 3. Weights calculated by averaging expert assessment

Criterion	Weight
Cost	0.25
Quality	0.30
Delivery	0.35
Service	0.10

2.7. Data Reliability and Validity

To improve data reliability, information collected from different departments was cross-checked before analysis. Supplier delivery records were compared with purchase orders and production schedules to verify consistency. The use of multiple operational data sources reduced the possibility of measurement errors and improved the validity of the analysis.

2.8. Sensitivity Analysis and Model Validation

Sensitivity analysis was conducted to examine the robustness of supplier rankings under different weighting conditions. The original criteria weights were systematically varied by ±10% and ±20%, and supplier rankings were recalculated. The stability of rankings across different scenarios was analyzed to determine whether the proposed framework produces consistent decisions.

Furthermore, the obtained supplier rankings were compared with a conventional MCDM method such as TOPSIS to validate the reliability of the proposed CRA-DA framework. The comparison demonstrated whether the proposed approach generated consistent supplier priorities while providing additional information regarding cost consequences.

2.9. Cost Ratio Analysis Method

The Cost Ratio Analysis (CRA) method is employed in this study to identify the most suitable suppliers by considering multiple evaluation criteria, including cost, quality, delivery performance, and service capability. This approach enables supplier selection based on the overall procurement cost rather than solely on the quoted purchase price. The cost analysis of ten candidate suppliers for the same product is presented in Table 4, and the net adjusted cost is calculated using Equation (1).

For illustration, Supplier A has a total penalty of 3%, while the quoted unit price is $1.10. Applying Equation (1), the net adjusted cost is calculated as.

{Net Adjusted Cost} = $1.10 \times (1 + 0.03) = $1.13

The same procedure is applied to all candidate suppliers to determine their respective net adjusted costs. Based on the analysis, Suppliers D, I, and J exhibit the lowest adjusted costs while satisfying the required quality, delivery, and service performance criteria. Therefore, these suppliers are selected as the preferred suppliers for Production Unit 1 (PU-1) to ensure cost-effective and reliable procurement.

$$\text{Net Adjusted cost} = \text{Quoted price/unit } (1 + \text{total penalty}) \tag{1}$$

Table 4. Implementation of cost ratio analysis method to select the right suppliers for PU-1

Supplier	Quality cost ratio	Delivery cost ratio	Service cost	Total Penalty	Quoted price/unit ($)	Net Adjusted cost
A	1%	1%	1%	3%	$1.10	$1.12
B	2%	1%	4%	6%	$1	$1.07
C	4%	3%	3%	7%	$1	$1.07
D	3%	1%	1%	6%	$1	$1.05
E	2%	2%	2%	4%	$1.12	$1.45
F	1%	2%	2%	3%	$1.05	$1.09
G	2%	3%	1%	6%	$1	$1.06
H	2%	1%	2%	4%	$1.03	$1.07
I	2%	1%	1%	4%	$1.02	$1.06
J	2%	2%	2%	6%	$0.90	$0.95

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At the same time, Table 5 portrays the suppliers' selection scenario for production unit 2. It is shown that suppliers D, F, and J are selected as the right suppliers to place the orders. In this way, the right suppliers can be selected for the manufacturing unit.

Table 5. Implementation of cost ration method to select the right suppliers for PU-2

Supplier	Quality cost ratio	Delivery cost ratio	Service cost	Total Penalty	Quoted price/unit ($)	Net Adjusted cost
A	2%	1%	1%	4%	$1.05	$1.09
B	2%	1%	2%	3%	$1.21	$1.23
C	1%	2%	2%	5%	$1.04	$1.10
D	1%	3%	1%	5%	$1	$1.04
E	1%	2%	3%	5%	$1.14	$1.21
F	2%	1%	2%	5%	$1.01	$1.06
G	2%	1%	2%	5%	$1	$1.17
H	2%	3%	1%	5%	$1.06	$1.11
I	2%	2%	1%	6%	$1.04	$1.11
J	2%	3%	2%	6%	$0.94	$1.02

2.10. Dimensional Analysis Method

In this paper, the dimensional analysis method is applied to pick the right supplier in real time for the apparel manufacturing industry to optimize the supply chain.

$$VPI = \sqrt{w \times \prod_{i=1}^{n} \left(\frac{X_i}{Y_i}\right)^{w_i}} \tag{2}$$

where,

VPI : Vendor Parameter Index

X_i : Performance criterion score achieved by the supplier for criterion i, where i = 1, 2, 3, …, n.

Y_i : Standard or target performance score for criterion i, where i = 1, 2, 3, …, n.

w_i : Weight representing the relative importance assigned to criterion i, where i = 1, 2, 3, …, n.

w : Total absolute weight, defined as:

$$w = \sum_{i=1}^{n} |w_i|$$

n : Total number of performance criteria.

In this research, the supplier selection process is analyzed using Equation 2. Table 6 shows that the VPI scores for suppliers A, B, and E are higher than any other for production unit 1. Hence, these three suppliers can be selected as the right suppliers. The demo calculation is given below for understanding the selection methodology using the dimensional analysis method.

VPI(A) = 14√ (0.98/1.00)6.(29/27)-5.(3/2)-3= 7.13

Similarly, the VPI scores of suppliers A and B are higher than the others. Thus, these two suppliers are selected as the best ones, which is depicted in Table 7 for manufacturing unit 2. The analysis is done for five suppliers who are supplying the same materials. By studying the selection criteria, the decision can be taken from such an analysis as to which one would be the best and right supplier.

Table 6. Implementation of dimensional analysis method to select the right suppliers for PU-1

	Quality (%)	Delivery (days)	Cost ($)	VPI
Weights	6	-5	-3	
Supplier A	98	29	3	7.13
Standard	100	27	2	
Weights	5	-2	-3	
Supplier B	80	33	3	5.36
Standard	100	27	2	
Weights	4	-5	-5	
Supplier C	70	35	3	1.25
Standard	100	27	2	
Weights	3	-6	-5	
Supplier D	60	31	3	1.53
Standard	100	27	2	
Weights	8	-3	-2	
Supplier E	99	28	3	8.51
Standard	100	27	2	

Table 7. Implementation of cost ration method to select the right suppliers for PU-2

	Quality (%)	Delivery (days)	Cost ($)	VPI
Weights	5	-6	-5	
Supplier A	95	21	3	9.49
Standard	100	27	2	
Weights	2	-5	-5	
Supplier B	85	23	3	6.41
Standard	100	27	2	
	Quality (%)	Delivery (days)	Cost ($)	
Weights	4	-2	-5	
Supplier C	78	25	3	3.31
Standard	100	27	2	
	Quality (%)	Delivery (days)	Cost ($)	
Weights	3	-4	-5	
Supplier D	75	38	3	1.59
Standard	100	27	2	
	Quality (%)	Delivery (days)	Cost ($)	
Weights	8	-3	-5	
Supplier E	65	35	3	0.07
Standard	100	27	2	

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3. Results and Discussion

3.1. Improvement in Benefit-to-Cost Ratio (BCR)

The economic effectiveness of the proposed supplier selection framework was evaluated using the Benefit-to-Cost Ratio (BCR). As presented in Fig. 4 and Fig. 5, Production Unit 1 experienced a considerable improvement in BCR after implementing the proposed CRA-DA-based supplier selection approach. Under the conventional supplier selection practice, the average BCR was approximately 1.10, indicating limited economic benefits due to delayed raw material deliveries, production interruptions, and additional logistics expenses. After selecting suppliers using the proposed framework, the BCR increased substantially, demonstrating that systematic supplier evaluation can reduce hidden procurement-related costs and improve overall supply chain value.

Similarly, Fig. 6 and Fig. 7 present the BCR improvement for Production Unit 2. The average BCR increased from approximately 0.90 under the conventional supplier selection approach to 2.00 after implementing the proposed framework. This improvement indicates that supplier selection based only on purchasing price may not provide the most economical solution because low-cost suppliers may generate additional expenses through delivery delays, production losses, and emergency procurement activities. The CRA component of the proposed framework identifies these economic consequences, while the DA component enables comparison of suppliers based on multiple operational criteria.

3.2. Improvement in Raw Material Delivery Performance

The impact of the proposed supplier selection framework on delivery reliability is illustrated in Fig. 8, Fig. 9, and Fig. 10. After replacing conventional suppliers with analytically selected suppliers, both production units achieved improved on-time raw material delivery performance. Production Unit 1 improved its delivery performance from 94% to 96%, while Production Unit 2 improved from 94% to 97%, as shown in Fig. 8. Furthermore, Fig. 9 and Fig. 10 demonstrate that the difference between promised delivery dates and actual receiving dates was significantly reduced after supplier re-evaluation. The selected suppliers provided more reliable delivery schedules, allowing manufacturers to maintain continuous production operations and minimize risks associated with material shortages. These findings confirm that evaluating suppliers based on historical delivery performance contributes to improved supply chain reliability.

3.3. Production Efficiency Improvement

The improvement in supplier reliability directly influenced production performance. As illustrated in Fig. 11 and Fig. 12, production efficiency increased by approximately 15–20% for Production Units 1 and 2 after implementing the proposed supplier selection framework. This improvement occurred because timely availability of raw materials reduced production waiting time, improved production planning accuracy, and minimized interruptions caused by material shortages.

The results indicate that supplier selection should not be considered only as a procurement activity but as a strategic manufacturing decision influencing productivity and operational performance. The proposed CRA-DA framework enables manufacturers to select suppliers based on their overall contribution to production efficiency rather than focusing only on initial purchasing cost.

3.4. Comparison with Existing Supplier Selection Approaches

A comparison of the proposed framework with commonly used supplier selection approaches is presented in Table 8. Existing methods such as AHP, TOPSIS, DEA, fuzzy MCDM, and artificial intelligence-based approaches provide effective supplier ranking capabilities; however, many of these methods primarily focus on relative performance evaluation and provide limited information regarding the economic consequences of supplier failures.

Table 8. Comparison of supplier selection approaches

Method	Main Advantage	Limitation	Difference from Proposed CRA-DA Framework
AHP	Effective criteria weighting	Subjective judgment dependency	CRA-DA incorporates delivery-related cost impact
TOPSIS	Efficient supplier ranking	Limited cost impact evaluation	CRA-DA links ranking with economic consequences
DEA	Measures supplier efficiency	Requires large datasets	CRA-DA is applicable with operational industrial data
ANN/GA	Predictive capability	High complexity and data requirements	CRA-DA provides transparent decision support
CRA-DA	Combines cost and performance evaluation	Requires accurate industrial data	Integrates economic and operational evaluation

3.5. Sensitivity and Robustness Analysis

To evaluate the reliability of the proposed framework, sensitivity analysis was conducted by modifying the weights of supplier evaluation criteria. The results presented in Table 9 demonstrate that the ranking order of suppliers remained stable under different weighting scenarios. This confirms that the selected suppliers were not influenced by a single criterion and that the proposed framework provides robust decision support.

Table 9. Sensitivity analysis of supplier ranking under different weighting scenarios

Scenario	Cost Weight	Quality Weight	Delivery Weight	Service Weight	Selected Supplier
Original	0.25	0.30	0.35	0.10	Supplier A
+10% Cost weight	0.30	0.28	0.33	0.09	Supplier A
-10% Cost weight	0.20	0.32	0.37	0.11	Supplier A
+10% Delivery weight	0.24	0.29	0.39	0.08	Supplier A
-10% Delivery weight	0.26	0.31	0.31	0.12	Supplier A

3.6. Managerial Implication

The findings provide important implications for apparel manufacturers. The proposed framework supports procurement managers in selecting suppliers based on measurable operational and economic performance rather than informal relationships or purchase price alone. By identifying reliable suppliers before procurement decisions are finalized, manufacturers can reduce material shortage risks, improve production planning, and enhance supply chain resilience. In Table 8, Compared with previous supplier-selection approaches based on fuzzy TOPSIS, ANN, and multi-criteria decision-making, the proposed framework provides comparable supplier evaluation while

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requiring significantly lower computational complexity. Furthermore, unlike previous studies that primarily focused on supplier ranking, this research demonstrates measurable improvements in operational performance, including increased on-time delivery, improved benefit-to-cost ratio, and higher production efficiency.

Overall, Fig. 4, Fig. 5, Fig. 6, Fig. 7, Fig. 8, Fig. 9, Fig. 10, Fig. 11, Fig. 12 and Table 1, Table 2, Table 3, Table 4, Table 5, Table 6, Table 7 and Table 8 demonstrate that integrating Cost Ratio Analysis and Dimensional Analysis provides a practical and reliable supplier evaluation framework for apparel manufacturing. The contribution of this study is not merely the application of existing analytical methods but the development and validation of an integrated decision-support approach that connects supplier selection with production cost minimization and operational improvement.

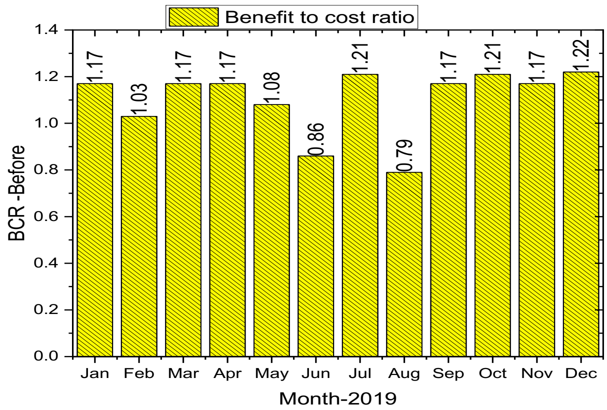


Fig. 4. Benefit -to-cost ratio analysis -before (PU-1)

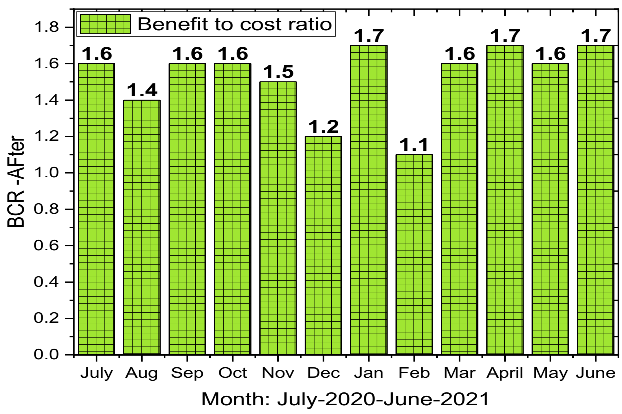


Fig. 5. Benefit -to-cost ratio analysis -after (PU-1)

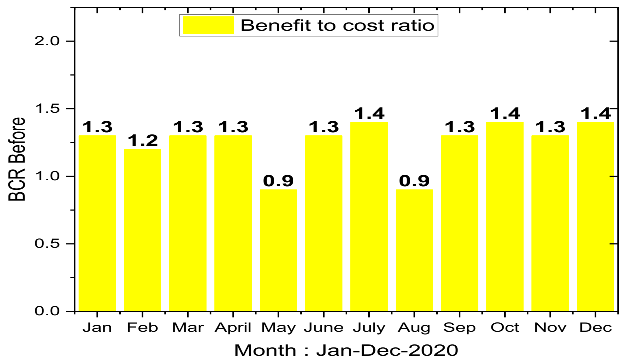


Fig. 6. Benefit -to-cost ratio analysis -after (PU-2)

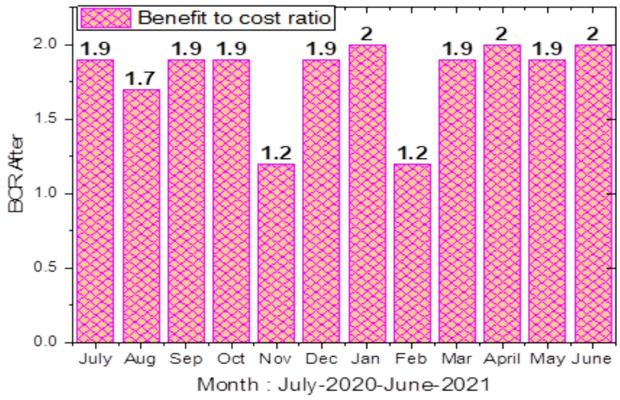
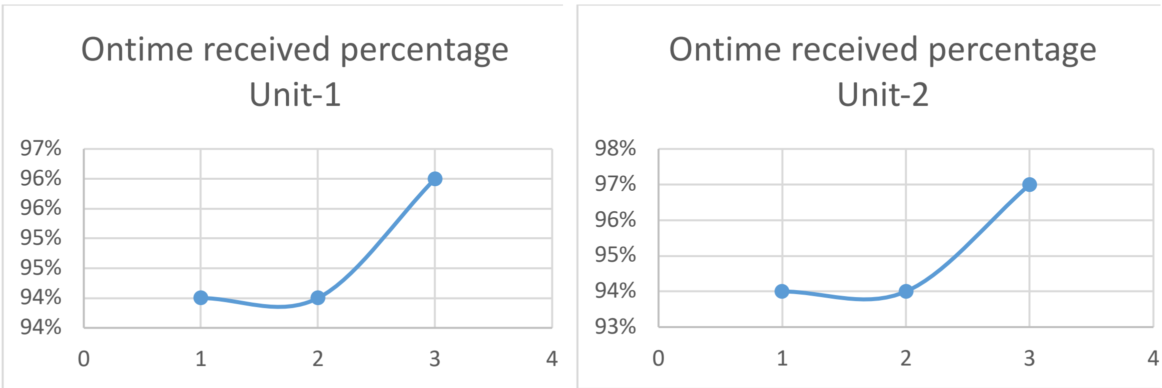


Fig. 7. Benefit -to-cost ratio analysis -after (PU-2)



(a) On time received percentage – Unit 1 (b) On time received percentage – Unit 2

Fig. 8. Ontime materials received status

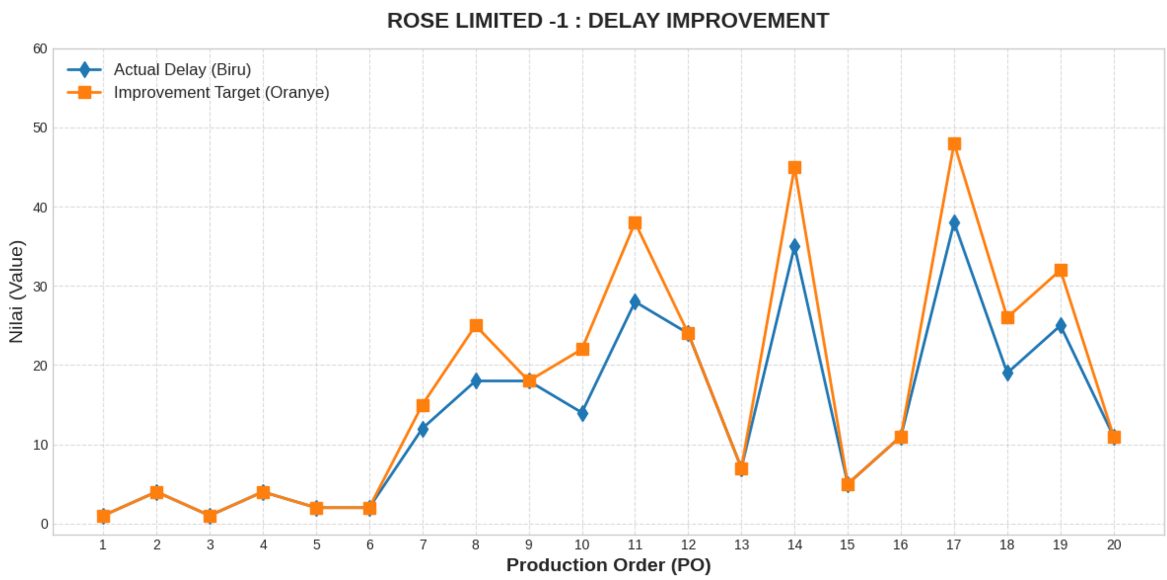


Fig. 9. Optimized delay improvements (PU-1)

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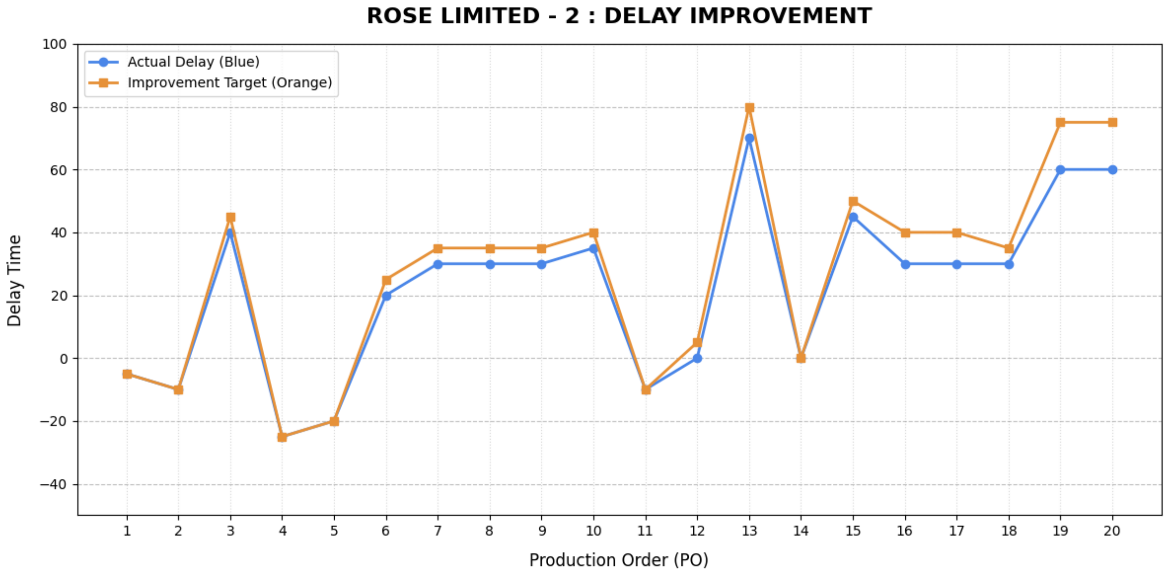

Fig. 10. Optimized delay improvements - (PU-2)

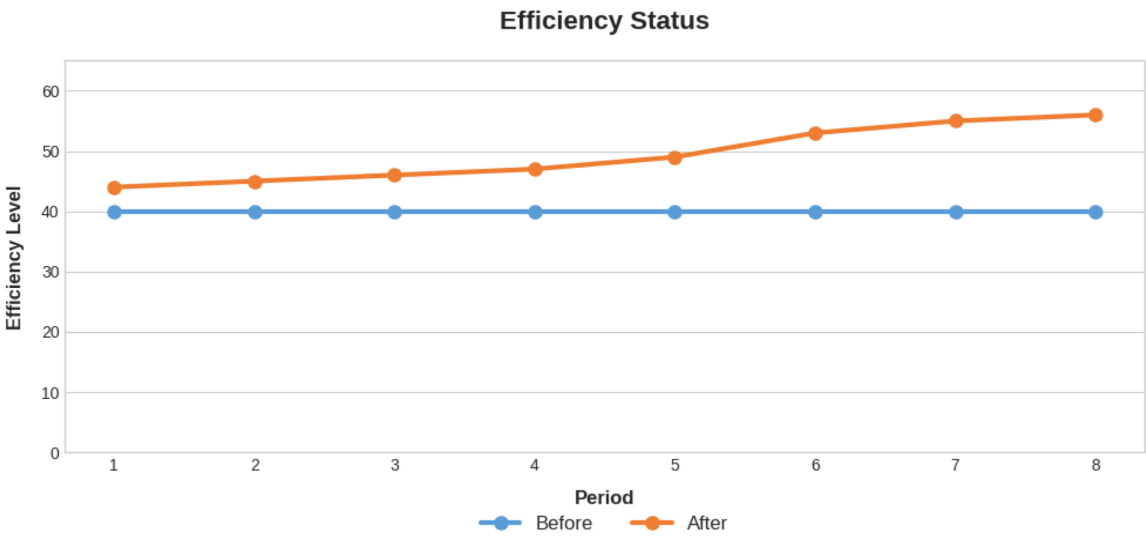

Fig. 11. Comparison of efficiency improvement status (PU-1)

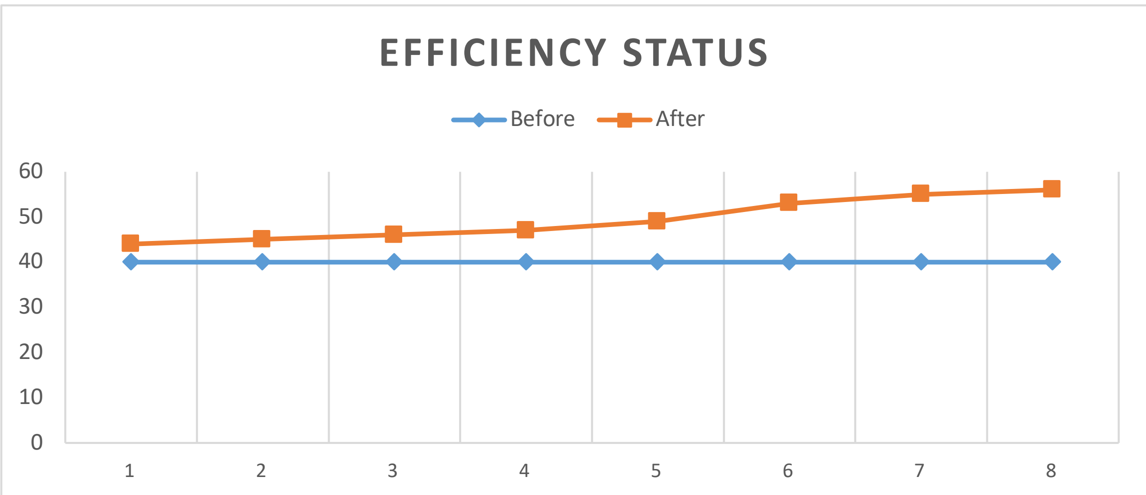

Fig. 12. Comparison of efficiency improvement (PU-1)

Several studies have proposed different approaches for supplier evaluation and selection in manufacturing industries. Liao and Kao employed the Fuzzy TOPSIS method to improve supplier ranking by incorporating uncertainty into the decision-making process. While their approach provides accurate supplier prioritization, it requires complex fuzzy calculations and expert-defined membership functions. In contrast, the proposed framework in this study utilizes a cost ratio combined with dimensional analysis, making it simpler to implement while being validated using real operational data from an apparel manufacturing factory. Similarly, Choy et al. [55] introduced an intelligent supplier evaluation system that significantly enhanced supplier management through advanced analytical techniques. Although their methodology effectively supports supplier selection, it primarily focuses on supplier evaluation. The present study extends this perspective by incorporating production efficiency and on-time delivery performance as key performance indicators, providing a more comprehensive assessment of supplier contribution to manufacturing performance.

Recent studies published between 2022 and 2025 [56]–[58] have increasingly applied Artificial Neural Network (ANN)-based models for supplier evaluation and performance prediction. These AI-driven approaches often achieve high prediction accuracy and improved supplier management. However, ANN models generally require large datasets, extensive computational resources, and specialized expertise for model development and interpretation. By comparison, the proposed cost ratio and dimensional analysis framework offers a practical, transparent, and computationally efficient alternative that can be readily adopted by apparel manufacturers without requiring sophisticated AI infrastructure. Overall, the proposed methodology demonstrates several practical advantages over previous approaches. Validation using industrial data indicates that the framework can support on-time delivery rates of approximately 94–97% while improving production efficiency by 15–20%. These results suggest that the proposed model not only facilitates effective supplier evaluation but also directly contributes to operational performance improvement, making it particularly suitable for apparel manufacturers seeking a simple, reliable, and industry-oriented supplier selection framework.

One of the major strengths of this study is its practical applicability. The framework is straightforward to understand, easy to implement, and requires relatively limited computational resources. Unlike ANN-based or fuzzy optimization models, the proposed approach does not require complex parameter tuning or large training datasets, making it particularly suitable for small and medium-sized apparel manufacturers that may lack advanced analytical capabilities. Another important strength is the validation of the methodology using real industrial data collected from an apparel manufacturing environment, thereby enhancing the practical relevance and credibility of the findings. The incorporation of both supplier evaluation and production performance metrics also provides managers with a more comprehensive decision-support tool than approaches focusing solely on supplier ranking.

However, this study also has several limitations. First, the validation was conducted using data from a single apparel manufacturing company, which may limit the generalizability of the findings across different industries or geographical regions. Second, the evaluation framework considers a limited number of performance indicators and does not explicitly include environmental sustainability, social responsibility, supplier resilience, or geopolitical risks, which have become increasingly important in modern supply chain management. Third, although the proposed method is computationally efficient, it may not capture highly nonlinear relationships among supplier attributes as effectively as advanced machine learning techniques such as Artificial Neural Networks or Deep Learning models. Consequently, its predictive capability may be lower in highly complex supply chain environments with large volumes of dynamic data.

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Compared with previous research, the proposed approach offers several important advantages. It provides a transparent and interpretable evaluation process, allowing managers to clearly understand how each performance criterion contributes to the final supplier assessment. The methodology is easier to implement than fuzzy or AI-based models and requires fewer computational resources while maintaining satisfactory operational performance. Moreover, its reliance on readily available production and procurement data facilitates practical adoption by manufacturing organizations without significant investment in specialized software or technical expertise. Nevertheless, compared with sophisticated machine learning models, the proposed approach may be less capable of identifying hidden patterns or adapting automatically to changing supply chain conditions. Therefore, organizations with extensive historical data and advanced analytical capabilities may still benefit from AI-driven decision-support systems.

The findings of this research have important implications for both industry and academia. For manufacturing practitioners, particularly in the apparel sector, the proposed framework offers a practical decision-support tool that can improve supplier evaluation, enhance production efficiency, and increase on-time delivery performance without requiring substantial technological investment. The methodology can support procurement managers in making more objective supplier selection decisions while simultaneously monitoring their impact on operational performance. For researchers, the study demonstrates that simple analytical techniques remain valuable alternatives to complex artificial intelligence methods, particularly when data availability or computational resources are limited. Future research may extend the proposed framework by integrating sustainability indicators, supplier risk assessment, digital supply chain technologies, Internet of Things (IoT) data, and advanced machine learning algorithms into a hybrid decision-support system. Validation across multiple manufacturing industries and larger datasets would further enhance the robustness and generalizability of the proposed methodology.

Overall, this study contributes to the supplier evaluation literature by presenting a practical, transparent, and industry-oriented framework that bridges the gap between supplier assessment and manufacturing performance. The results suggest that organizations can achieve substantial operational improvements through systematic supplier evaluation without necessarily adopting highly complex computational models, thereby providing an effective balance between methodological simplicity and practical effectiveness.

4. Conclusion

This study investigated the impact of systematic supplier selection on supply chain performance and production cost minimization in apparel manufacturing. The findings demonstrate that supplier reliability, particularly in terms of delivery performance, quality, and cost impact, plays a critical role in maintaining continuous production operations. The proposed integrated framework combining Cost Ratio Analysis (CRA) and Dimensional Analysis (DA) was developed to support supplier evaluation by considering both economic consequences of supplier performance and multiple operational criteria.

The proposed framework was validated using real industrial data collected from two apparel manufacturing facilities in Bangladesh. The results indicate that applying a structured supplier evaluation approach improved supplier performance, increased the Benefit-to-Cost Ratio (BCR), enhanced on-time raw material delivery, and contributed to improved production efficiency. These findings suggest that data-driven supplier selection can provide more reliable procurement decisions compared with conventional approaches that primarily depend on purchasing price or informal supplier relationships.

The theoretical contribution of this study lies in extending supplier selection research by integrating two complementary perspectives: economic impact assessment and multi-criteria supplier evaluation. While existing supplier selection studies frequently focus on ranking suppliers using individual decision-making techniques, this research demonstrates the importance of linking supplier performance evaluation with measurable production-related cost consequences. Therefore, the contribution of this study is not the introduction of a new mathematical method but the development and empirical validation of an integrated decision-support framework for cost-oriented supplier selection in apparel manufacturing. From a managerial perspective, the proposed framework provides manufacturers with a transparent and practical approach for supplier assessment, strategic sourcing, and supply chain risk reduction. By identifying suppliers based on overall performance rather than only purchase price, organizations can improve material availability, reduce production interruptions, and enhance operational competitiveness.

However, several limitations should be acknowledged. First, the framework was validated using data from only two apparel manufacturing facilities; therefore, the generalizability of the findings may be limited to similar industrial contexts. Second, the study focuses primarily on cost, quality, delivery, and service-related criteria, while other factors such as sustainability, supplier innovation capability, environmental performance, and supply chain risk were not included. Third, the weighting assumptions used in supplier evaluation may influence ranking outcomes, requiring further validation under different decision scenarios.

Future research should expand the proposed framework by incorporating larger datasets from multiple industries and geographical regions. Comparative studies using advanced multi-criteria decision-making approaches, including fuzzy TOPSIS, AHP, VIKOR, Best-Worst Method, and DEA, can provide further insights into the relative effectiveness of different supplier evaluation strategies. In addition, integrating artificial intelligence, machine learning, predictive analytics, multi-objective optimization, and dynamic supplier evaluation models could enhance the adaptability of supplier selection systems and support real-time decision-making in increasingly complex global supply chains.

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References

[1] S. Akter, "Clean Manufacturing and Green Practices in the Apparel Supply Chain," *Open J. Bus. Manag.*, vol. 08, no. 01, pp. 104–113, 2020, doi: 10.4236/ojbm.2020.81007.

[2] C.-N. Liao and H.-P. Kao, "An integrated fuzzy TOPSIS and MCGP approach to supplier selection in supply chain management," *Expert Syst. Appl.*, vol. 38, no. 9, pp. 10803–10811, Sep. 2011, doi: 10.1016/j.eswa.2011.02.031.

[3] V. Y. Tokala and N. Dubey, "Effective Supply Chain Management: A Way Forward for Sustainability and Food Security," *Adv. Postharvest Anal. Technol. of Horticulture Crops*, 2024, doi: 10.1007/978-981-97-7247-6_16.

[4] D. D. Wu, Y. Zhang, D. Wu, and D. L. Olson, "Fuzzy multi-objective programming for supplier selection and risk modeling: A possibility approach," *Eur. J. Oper. Research*, 2010,

[5] R. Verma and M. E. Pullman, "An analysis of the supplier selection process," *Omega*, vol. 26, no. 6, pp. 739–750, Dec. 1998, doi: 10.1016/S0305-0483(98)00023-1.

[6] K. Chugh, P. Gupta, A. Dhall, and R. Subramanian, "Not made for each other-audio-visual dissonance-based deepfake detection and localization," *Proc. 28th ACM International Conference on Multimedia*, 2020, doi: 10.1145/3394171.3413700.

[7] K. S. Bhutta and F. Huq, "Supplier selection problem: a comparison of the total cost of ownership and analytic hierarchy process approaches," *Supply Chain Manag. An Int. J.*, vol. 7, no. 3, pp. 126–135, Aug. 2002, doi: 10.1108/13598540210436586.

[8] F. Çebi and D. Bayraktar, "An integrated approach for supplier selection," *Logist. Inf. Manag.*, vol. 16, no. 6, pp. 395–400, Dec. 2003, doi: 10.1108/09576050310503376.

[9] L. de Boer, E. Labro, and P. Morlacchi, "A review of methods supporting supplier selection," *Eur. J. Purch. Supply Manag.*, vol. 7, no. 2, pp. 75–89, Jun. 2001, doi: 10.1016/S0969-7012(00)00028-9.

[10] S. Talluri, "A buyer–seller game model for selection and negotiation of purchasing bids," *Eur. J. Oper. Res.*, 2002, doi: 10.1016/S0377-2217(01)00333-2.

[11] K. L. Choy, W. B. Lee, and V. Lo, "Design of a case based intelligent supplier relationship management system—the integration of supplier rating system and product coding system," *Expert Syst. Appl.*, 2003, [Online]. Available: 10.1016/S0957-4174(03)00009-5.

[12] J. Zhu, "A buyer–seller game model for selection and negotiation of purchasing bids: Extensions and new models," *Eur. J. Oper. Res.*, vol. 154, no. 1, pp. 150–156, Apr. 2004, doi: 10.1016/S0377-2217(02)00697-5.

[13] F. M. Alam, K. R. McNaught, and T. J. Ringrose, "A comparison of experimental designs in the development of a neural network simulation metamodel," *Simul. Model. Pract. Theory*, vol. 12, no. 7–8, pp. 559–578, Nov. 2004, doi: 10.1016/j.simpat.2003.10.006.

[14] S. Terzi and S. Cavalieri, "Simulation in the supply chain context: a survey," *Comput. Ind.*, vol. 53, no. 1, pp. 3–16, Jan. 2004, doi: 10.1016/S0166-3615(03)00104-0.

[15] H.-G. Beyer and B. Sendhoff, "Robust optimization – A comprehensive survey," *Comput. Methods Appl. Mech. Eng.*, vol. 196, no. 33–34, pp. 3190–3218, Jul. 2007, doi: 10.1016/j.cma.2007.03.003.

[16] S. Haykin, "Neural networks: a comprehensive foundation. 1999," *Mc Millan, New Jersey*. 2010.

[17] L. G. Papageorgiou, "Supply chain optimisation for the process industries: Advances and opportunities," *Comput. Chem. Eng.*, vol. 33, no. 12, pp. 1931–1938, Dec. 2009, doi: 10.1016/j.compchemeng.2009.06.014.

[18] S. Croom, P. Romano, and M. Giannakis, "Supply chain management: an analytical framework for critical literature review," *European Journal of Purch. &supply Manag.*, 2000, doi: 10.1016/S0969-7012(99)00030-1.

[19] S. K. Srivastava, "Green supply-chain management: A state-of-the-art literature review," *Int. J. Manag. Rev.*, vol. 9, no. 1, pp. 53–80, Mar. 2007, doi: 10.1111/j.1468-2370.2007.00202.x.

[20] M. J. Meixell and V. B. Gargeya, "Global supply chain design: A literature review and critique," *Transp. Res. Part E Logist. Transp. Rev.*, vol. 41, no. 6, pp. 531–550, Nov. 2005, doi: 10.1016/j.tre.2005.06.003.

[21] P. D. Cousins, B. Lawson, and B. Squire, "An empirical taxonomy of purchasing functions," *Int. J. Oper. Prod. Manag.*, vol. 26, no. 7, pp. 775–794, Jul. 2006, doi: 10.1108/01443570610672239.

[22] M. Pohl and K. Förstl, "Achieving purchasing competence through purchasing performance measurement system design—A multiple-case study analysis," *J. Purch. Supply Manag.*, vol. 17, no. 4, pp. 231–245, Dec. 2011, doi: 10.1016/j.pursup.2011.04.001.

[23] D. A. R. Balida, A. I. Merchant, E. Abdullayev, and A. Altwaijri, "Assessing Awareness and Compliance of Health and Safety Standards by Construction Workers in Al Khobar, Saudi Arabia," *Sustainable Data Management*, 2025, doi: 10.1007/978-3-031-83915-3_15.

[24] S. Ahmad, M. Kamruzzaman, and M. M. Bappy, "Supply chain optimization in apparel manufacturing," *Proceedings of the International Conference on Industrial Engineering and Operations Management*. ieomsociety.org, 2019, [Online]. Available: http://ieomsociety.org/toronto2019/papers/319.pdf.

[25] S. Ahmad and M. Kamruzzaman, "Supply chain optimization with Genetic Algorithm focusing on right supplier selection at real time in apparel manufacturing," *4th North American International Conference on Industrial Engineering and Operations Management, Toronto, Canada*. ieomsociety.org, 2019, [Online]. Available: https://ieomsociety.org/toronto2019/papers/358.pdf.

[26] S. Ahmad, M. Kamruzzaman, M. S. Hossain, and M. M. Rahman, "Apparel supply chain optimization by developing e-commerce: An impact analysis," *4th North American International Conference on Industrial Engineering and Operations Management, Toronto, Canada*. ieomsociety.org, 2019, [Online]. Available: http://ieomsociety.org/toronto2019/papers/318.pdf.

[27] S. Ahmad, M. Kamruzzaman, and M. Iqbal, "Impacts of optimization in apparel supply chain focusing on ANN and Genetic Algorithm," *Proceedings of the International Conference on Industrial Engineering and Operations Management*. ieomsociety.org, 2020, [Online]. Available: http://www.ieomsociety.org/detroit2020/papers/770.pdf.

[28] P. Manne, S. Ahmad, and J. Waterman, "Design and development of mine railcar components," *American Journal of Mechanical Engineering*. 2016.

[29] A. R. Chowdhury, A. M. Mithu, S. Ahmad, and A. A. Malek, "A Data-Driven Approach to Inventory Control under Uncertain Demand for Pharmaceutical Products Using Continuous Review Policy," *International Journal of Business & Management*. 2024. doi: 10.5281/zenodo.10700678

[30] B. Shen, C. Zhu, Q. Li, and X. Wang, "Green technology adoption in textiles and apparel supply chains with environmental taxes," *Int. J. Prod. Research*, 2021, doi: 10.1080/00207543.2020.1758354.

[31] M. A. Azad, "Optimizing supply chain efficiency through lean six sigma: Case studies in textile and apparel manufacturing," *Preprints*. 2025, doi: 10.20944/preprints202508.0013.v1.

[32] S. Ahmad, "Effect of Some Selected Factors on Job Satisfaction in Public Banking," *IOSR J. Bus. Manag.*, vol. 5, no. 3, pp. 41–46, 2012, doi: 10.9790/487X-0534146.

[33] S. Ahmad, N. Bagum, C. A. Rashed, A. B. Khalil, and M. Iqbal, "The impacts of alb in apparel supply chain," *Journal Of Management Sciences*. 2012.

[34] S. Ahmad, M. M. Rashid, M. Iqbal, and M. A. R. Sarkar, "Ergonomics for Tabloid Chair Manufacturing," *International Journal of Ergonomics*. 2021.

[35] S. Ahmad and M. Kamruzzaman, "Analysis of Availability of Fire Fighting Equipment in Selected Knitting Garment Factories in Bangladesh," *Proceedings of the 2015 International Conference on Operations Excellence and Service Engineering*. ieomsociety.org, 2015, [Online]. Available: https://ieomsociety.org/IEOM_Orlnado_2015/papers/261.pdf.

[36] S. Ahmad and M. Kamruzzaman, "Supplier Selection and Evaluation using Genetic Algorithm: A Case Study in an Apparel Manufacturing Organization," *International Conference on Mechanical Manufacturing and Process Engineering*. 2022.

 10.12928/ijio.v7i2.14381

[37] J. R. Nalbach *et al.*, “Fabrication of Tunable Silk Materials Through Microfluidic Mixers,” Nov. 2016, doi: 10.1115/IMECE2016-65623.

[38] S. Ahmad and M. Kamruzzaman, “Supplier Selection and Evaluation in Apparel Industry,” *Journal of Business Management and Economic Research*, 2022, doi: 10.29226/TR1001.2022.296.

[39] S. N. Jahan, M. K. Ahmed, A. A. Rabbi, S. Ahmad, and N. Akter, “AI-Based Garments Manufacturing,” *Advances in Artificial Intelligence and Robotics Research*. 2026, doi: 10.4236/airr.2026.22003.

[40] S. N. Jahan, M. K. Ahmed, A. A. Rabbi, and S. Ahmad, “The Role of AI in Apparel Manufacturing,” *Eur. J. Logist. Purch. Supply Chain Manag.*, vol. 14, no. 1, pp. 36–51, Jan. 2026, doi: 10.37745/ejlpscm.2013/vol14n13651.

[41] S. N. Jahan, M. K. Ahmed, A. A. Rabbi, S. Ahmad, N. Akter, and M. Iqbal, “Implications of Cloud Computing in the American Automobile Manufacturing.” 2026, doi: 10.5281/zenodo.20472931.

[42] S. Ahmad and M. Kamruzzaman, “Inspection cost minimization by optimizing the number of inspectors in apparel manufacturing,” *Int. J. Ind. Optim.*, vol. 6, no. 1, pp. 71–86, Mar. 2025, doi: doi.org/10.12928/ijio.v6i1.9279.

[43] S. Ahmad and M. Kamruzzaman, “Mathematical Analysis of Supply Chain Optimization focusing on Artificial Neural Network: A case study in Apparel Manufacturing Organization.” Jan. 03, 2022, doi: 10.21203/rs.3.rs-1173130/v1.

[44] C.-N. Wang, V. T. H. Viet, T. P. Ho, V. T. Nguyen, and V. T. Nguyen, “Multi-Criteria Decision Model for the Selection of Suppliers in the Textile Industry,” *Symmetry (Basel).*, vol. 12, no. 6, p. 979, Jun. 2020, doi: 10.3390/sym12060979.

[45] S. S. Sithi, M. A. Ara, A. T. Dhrubo, A. H. Rony, and M. A. Shabur, “Sustainable supplier selection in the textile industry using triple bottom line and SWARA-TOPSIS approaches,” *Discover Sustainability*. Springer, 2025, doi: 10.1007/s43621-025-01206-9.

[46] M. A. Ara, M. S. Tamanna, M. Ali, A. Amin, and M. A. Shabur, “A hybrid AHP and statistical validation approach for sustainable supplier selection in apparel industry,” *Discover Sustainability*. Springer, 2025, doi: 10.1007/s43621-025-01416-1.

[47] N. N. Phan Ha, D. D. Nguyen, and S. T. Q. Le, “Sustainable supplier selection in the apparel industry: an integrated AHP-TOPSIS model for multi-criteria decision analysis,” *Res. J. Text. Appar.*, vol. 29, no. 4, pp. 822–841, Nov. 2025, doi: 10.1108/RJTA-04-2024-0056.

[48] M. Ahmad, S. and Kamruzzaman, “Optimization in apparel supply chain using Artificial Neural Network,” *Eur. J. Logist. Purch. Supply Chain Manag.*, vol. 10, no. 1, pp. 1–14, Feb. 2022, doi: 10.37745/ejlpscm.2013/vol10no1pp.1-14.

[49] S. Ahmad, “A Review on Inspection Cost Minimization by Optimal Number Inspectors in Apparel Manufacturing,” Jun. 2023, doi: 10.46254/NA8.20230318.

[50] N. U. H. Qureshi, S. Javed, K. Javed, S. M. R. Naqvi, and Z. Saeed, “Demand forecasting in supply chain management for rossmann stores using weather enhanced deep learning model,” *IEEE Access*, 2024, doi: 10.1109/ACCESS.2024.3472499.

[51] N. J. Sheikh, K. Ahmed, A. A. Rabbi, and S. Ahmad, “E-commerce and its impact on supply chain: An analysis in apparel manufacturing,” *World Journal of Artificial and Rob Res*. 2024.

[52] S. N. Jahan, M. K. Ahmed, A. A. Rabbi, S. Ahmad, and A. M. Mithu, “Optimizing it Efficiency and Sustainability: Hybrid Cloud Migration for Greentech Innovations,” *Int. J. Comput. Eng. Technol.*, vol. 16, no. 4, pp. 30–53, Jul. 2025, doi: 10.34218/IJCET_16_04_003.

[53] A. Mohammad, S. Ahmad, and M. Iqbal, "Identification of retention time & information delays applying value stream mapping technique in apparel manufacturing organization," *Proc. 2015 Int. Conf. Oper. Excell. Serv. Eng. Orlando, Florida, USA, Sept.*, pp. 10–11, 2015.

[54] A. M. Mohammad, S. Ahmad, M. Iqbal, and M. Alauddin, "Inventory Reduction by Applying Inventory Management Tools of a Selected Tannery Factory," *J. Bus. Econ.*, vol. 6, no. 1, pp. 204–210, Jan. 2015, doi: 10.15341/jbe(2155-7950)/01.06.2015/019.

[55] K. L. Choy, W. B. Lee, and V. Lo, "Design of an intelligent supplier relationship management system: a hybrid case based neural network approach," *Expert Syst. Appl.*, 2003, doi: 10.1016/S0957-4174(02)00151-3.

[56] H. Kao, "Integrated Fuzzy-MSGP Methods for Clothing and Textiles Supplier Evaluation and Selection in the COVID-19 Era," *Math. Probl. Eng.*, vol. 2022, pp. 1–13, Jul. 2022, doi: 10.1155/2022/9433454.

[57] Y. Deng and F. T. S. Chan, "A new fuzzy dempster MCDM method and its application in supplier selection," *Expert Syst. Appl.*, vol. 38, no. 8, pp. 9854–9861, Aug. 2011, doi: 10.1016/j.eswa.2011.02.017.

[58] Y. Li, X. Liu, and Y. Chen, "Supplier selection using axiomatic fuzzy set and TOPSIS methodology in supply chain management," *Fuzzy Optim. Decis. Mak.*, vol. 11, no. 2, pp. 147–176, Jun. 2012, doi: 10.1007/s10700-012-9117-x.

 10.12928/ijio.v7i2.14381